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Dynamic Cosine Method for Normalizing Incidence Angle Effect on C-band Radar Backscattering Coefficient for Maize Canopies Based on NDVI

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Abstract: Wide mode SAR images have an apparent incidence angle effect. The existing incident angle normalization methods assume that the relationship between the incident angle (θ) and the backscattering coefficient (σ_{PQ}) does not change with the growth stage of crops, which is in conflict with the real-life situation. Therefore, the normalization results of σ_{PQ} based on these existing methods will affect the accuracy of object classification, target recognition, and land surface parameter inversion. Here, the change in θ - σ_{PQ} relationship was investigated based on time-series (April to October) σ_{PQ} of maize canopies in northeast China, and a dynamic method based on normalized difference vegetation index (NDVI) was developed to normalize the effect of θ on σ_{PQ} . Through the accuracy evaluation, the following conclusions are obtained: (1) the dependence (referring to N) of Sentinel 1 C-band σ_{PQ} on θ varies with maize NDVI. In addition, the value of N changed from 9.35 to 0.66 at VV polarization from bare soil to biomass peak, and from 6.26 to 0.99 at VH polarization; (2) a dynamic method was proposed to quantify the change of N based on its strong correlation with NDVI, indicated by R^2 of 0.82 and 0.80 for VV and VH polarization, respectively; and (3) the overall root mean square error of normalized σ_{PQ} based on the newly-developed dynamic method is 0.51 dB, and this accuracy outperforms the original first-order cosine method (1.37 dB) and cosine square law method (1.08 dB) by about 63% and 53% on the whole. This study provides a dynamic framework for normalizing radar backscatter coefficient, improving the retrieval accuracy of land surface parameters from radar remote sensing.

Keywords: Sentinel-1&2; SAR; incident angle effect; angle normalization; NDVI; maize

1. Introduction

SAR data are often used for land cover classification, target detection, and land surface parameter retrievals (leaf area index, snow water equivalent, and soil moisture) [1–3]. However, radar backscattering coefficient (σ^0) changes with incident angle (θ) [4,5], show significant θ effect. For example, Radarsat σ^0 of C-band Radarsat image changes 0.26 dB/° for a snow covered surface when θ ranges from 23° to 45° [6,7]. This incidence angle effect would reduce the accuracy of crop classification and soil moisture estimation based on change detection [8,9].

The dependence of σ^0 on θ is related to polarization, land cover type, and crop growth stage [10–12]. At present, there are three methods for normalizing the radar incidence

angle effect, including histogram matching method [13,14], linear method, and cosine method [15]. The histogram matching method is easy to apply, it only requires little prior knowledge, and its performance does not depend on sensor characteristics and ground conditions [10]. However, its normalized result may appear discontinuous in the range direction of the Radar image [11]. The linear method ignores the complex physical mechanism between σ^0 and θ [16]. Furthermore, it requires a large number of auxiliary parameters and its normalized accuracy is higher in a specific study area, with poor portability [10]. The cosine model is derived from Lambert's law [15], indicating the relationship between σ^0 and θ obeys the law of cosine; it shows better performance for the homogeneous pixel.

The cosine method is one of the widely used normalization methods, first proposed by Clapp to eliminate the change of σ^0 caused by θ [17]. It assumes that the amount of power reradiated in the upper hemisphere obeys the law of cosine [15]. Its formula is $\sigma\theta = \sigma^0 \cos^N(\theta)$, σ^0 is the backscattering coefficient independent of θ , and N is the power exponent of the cosine function, adjusting the dependence of σ^0 on θ . The traditional cosine method adopts fixed N ($N = 0, 1, 2$), and this assumption cannot be well met for different ground features because the angle dependence of σ^0 is affected by many factors.

Some studies have proven that radar parameters (polarization), land cover type, and crop growth stage are the important factors affecting the dependence of σ^0 on θ [18–20], revealing the various N value in different cases. In terms of polarization, the N of non-irrigated olive trees is 6.3 and 5.5 for VV and HH polarization, respectively [21], and different N values are obtained for wetlands at different polarization modes (HH:2.4–2.5; VH:1.4–2.2; VV:2.1–2.8) [22]. In terms of land cover type, L-band ScanSAR image showed that the value of N for rainforest land cover types ranged from 0.24 to 3.36 [18], and another N value ($N = 1.55$) suitable for forest area is obtained [23]. The above results confirmed that the N value changes with forest types. The method considering the angle variation of σ^0 for most land cover types was proposed, and successfully normalized the angle of vegetation communities in the Australian savanna landscape from radar images [24]. The angular dependence of ASAR WS backscatter is found to vary strongly over cropland [25]. Moreover, Lang et al. (2016) found that open water bodies and different types of ice affect the dependence of σ^0 on θ [11]. In accordance with crop growth stage, the crop growth stage is seasonal in most cases [26], which leads to σ^0 varying seasonally on the angle dependence. The dependence of σ^0 on θ varies greatly in farmland, but little in permanent vegetation [25].

Summarizing the above results, it is found that a fixed N value is not suitable for changing land surface types, growth stages, and radar polarization modes. In agricultural areas, the dependence of σ^0 on θ is mainly affected by crop types and crop growth stages. Aiming to reduce errors of normalized σ^0 , a NDVI (normalized difference vegetation index) representing the changes of crop growth stage, was used to quantify the angular sensitivity of radar signals [25]. The results show that NDVI has great potential in characterizing the angular sensitivity of C-band σ^0 for wheat [27]. Although it has been recognized that the dependence of σ^0 on θ is dynamic, the incidence angle normalization model of σ^0 considering this dynamic change is rare. The biomass of maize is much larger than that of soybean and wheat in the whole growth stage, which has a great influence on radar signal scattering. This is helpful for us to study the influence of plant canopy on electromagnetic wave scattering from bare soil stage to maturity stage. To solve this problem, we plan to take maize as an example to investigate the relationship between σ^0 and θ , and establish a general incidence angle normalization method of σ^0 suitable for different crop growth stages, so as to improve the ability of radar data in ground object classification, target detection and land surface parameter retrievals.

This paper aims to investigate the variation characteristics of σ^0 with respect to θ , and evaluates the angle normalization effect of cosine methods. In addition, a dynamic cosine model for incidence angle normalization of σ^0 was proposed. This paper is composed of the following parts: Section 2 describes the study area, data sets and methods; Section 3

analyzes the relationship between σ^0 and θ for maize and proposes and evaluates a new dynamic cosine method; Section 4 discusses the advantages and disadvantages of the newly proposed method; and Section 5 provides the conclusion.

2. Data and Methods

2.1. Study Site and Data Sets

2.1.1. Study Areas

The study site is located in the central part of Jilin Province in northeast China ($123^{\circ}08' \sim 127^{\circ}09' \text{ E}$, $43^{\circ}10' \sim 44^{\circ}51' \text{ N}$) with an area of approximately $250 \text{ km} \times 160 \text{ km}$, covering Changchun, Songyuan, Siping, and Jilin city (Figure 1). It belongs to the hinterland of the Songliao Plain in northeast China. It is one of the most important commercial maize production bases in China, and one of the three major black soil regions as well as three golden maize belts in the world [28]. Maize is the main crop in the study area, and the maize planting area accounts for 74.8% of the total crop area. The study area has a temperate continental monsoon climate, with four distinct seasons, including hot and rainy seasons. The average annual sunshine duration ranges from 2259 to 3016 h, and the average annual precipitation ranges from 400 to 600 mm. Due to the flat terrain (102–398 m) in the study area, the terrain variability in terms of slope was not taken into account [15].

Figure 1. Location of the study area. (a) The red box represents the scope of the study area, which is located in the farmland area in the middle of Jilin Province; (b) the digital elevation map of the study area; and (c) the land cover classification from GlobeLand30 (<http://www.globallandcover.com> (accessed on 01 June 2021)).

2.1.2. Description of the Sentinel-1 and Sentinel-2 Data

This study used 10 m spatial resolution GRD (ground range detected) data in Sentinel-1 IW (interferometric wide swath) mode. The data were obtained from the Sentinel Satellite Data Distribution Network of the European Space Agency (ESA, <https://scihub.copernicus.eu/dhus/#/home> (accessed on 01 June 2021)). A total of 12 images were collected, spanning from April to October of 2019 (Table 1), covering the whole growing season of maize (seeding, seedling emergence, jointing, tasseling, flowering, silking, and maturity) [29,30]. The Sentinel-1 satellite only has descending passes on data in the study area. The θ of

time-series SAR images ranged from 31° to 46° . Sentinel-1 data were preprocessed by the ESA's SNAP (Sentinel Application Platform) software with orbit correction, radiometric calibration, multi-looking, filtering, and terrain correction. In order to reduce the noise, the Sentinel-1 data after terrain correction were resampled to 1 km. Although the study area is dominated by maize planting, the internal water body and built-up area will interfere with the relationship between σ^0 and θ . Therefore, the 30 m resolution global land cover data product is resampled to 1 km, and its farmland products are used to mask the SAR data.

Table 1. The difference of backscattering coefficients ($\Delta\sigma^0$) corresponding to incident angles of 31° and 46° in the time series Sentinel-1 C-band radar data.

Sentinel-1 Acquisition Date	DOY	$\sigma_{vv}^0(31^\circ)$	$\sigma_{vv}^0(46^\circ)$	$\Delta\sigma_{vv}^0$	$\sigma_{vh}^0(31^\circ)$	$\sigma_{vh}^0(46^\circ)$	$\Delta\sigma_{vh}^0$
2019-04-19	109	−11.06	−17.11	6.05	−20.22	−22.90	2.68
2019-05-13	133	−9.23	−17.02	7.79	−18.47	−22.83	4.35
2019-06-06	157	−9.12	−15.29	6.17	−18.49	−21.49	3.00
2019-06-18	169	−9.44	−13.26	3.82	−17.56	−20.58	3.02
2019-06-30	181	−7.04	−10.44	3.41	−13.91	−17.21	3.30
2019-07-12	193	−7.97	−10.28	2.31	−14.22	−16.93	2.71
2019-07-24	205	−7.95	−9.90	1.95	−14.07	−15.73	1.66
2019-08-17	229	−8.04	−9.29	1.25	−14.10	−15.05	0.94
2019-09-10	253	−8.09	−11.16	3.07	−15.06	−16.95	1.90
2019-09-22	265	−8.42	−11.59	3.17	−15.16	−17.75	2.59
2019-10-04	277	−9.02	−12.99	3.97	−15.52	−19.65	4.13
2019-10-16	289	−9.92	−14.95	5.03	−18.07	−21.53	3.46

Note: The unit of backscattering coefficients is dB.

The Sentinel-2 data used in this study are a Level-2 A 10 m spatial resolution product preprocessed by radiation calibration and atmospheric correction, and the data were obtained from the ESA Sentinel Satellite Data Distribution Network (<https://scihub.copernicus.eu/dhus/#/home> (accessed on 01 June 2021)). We generated the NDVI data using the ESA SNAP software. Under ideal conditions, the collaborative use of optical and radar data usually requires the same temporal and spatial resolution. In order to solve the problem of cloud cover and date mismatch between the optical and radar product, the Savitzky–Golay filter was used to obtain NDVI [31,32]. Sentinel-2 data were resampled and masked in the same way with Sentinel-1 data.

Figure 2 shows preprocessed sentinel-1 VV polarization images, and a representative image is selected for each month. σ^0 shows a significant overall changing trend with θ in April, May, June, and October, while a weak change exists in July, August, and September. σ_{46}^0 and σ_{31}^0 represent σ^0 at the maximum (46°) and minimum (31°) incident angles, respectively. The incidence angle effect $\Delta\sigma^0$ is defined ($\Delta\sigma^0 = \sigma_{31}^0 - \sigma_{46}^0$). The statistical results of each date for VV and VH polarization are provided in Table 1. $\Delta\sigma^0$ is larger in April, May, June, September, and October, and is smaller in July and August for VV and VH polarization. This is consistent with O'Grady's conclusion [33]. In general, the trend of $\Delta\sigma^0$ first decreases and then increases with time, which is consistent with Fieuzal et al. (2013) [27]. In VV polarization, the maximum $\Delta\sigma^0$ (7.79 dB) appears in the bare soil period (DOY = 133); the minimum $\Delta\sigma^0$ (1.25 dB) appears in the tassle to silking period (DOY = 229). A similar result was achieved for VH polarization.

Figure 2. The multi-temporal Sentinel-1 VV polarization backscattering coefficient after being pre-processed in the study area. The incidence angle of each image is 31–46° from right to left.

2.2. Incidence Angle Normalization Method

2.2.1. Overview of Cosine Method

Cosine model expression is shown in Equation (1) [15]:

$$\sigma_{norm}^0 = \sigma_{\theta}^0 \left(\frac{\cos \theta_{norm}}{\cos \theta} \right)^N \quad (1)$$

where θ_{norm} is the normalized angle, and σ_{norm}^0 represents the normalized σ^0 . σ_{θ}^0 obtained at θ can be normalized to σ_{norm}^0 with any angle. N is the power exponent of the cosine function, adjusting the dependence of σ^0 on θ . The fixed N is usually set to 1, 2. When $N = 1$, the cosine model is called a first-order cosine method. It corresponds to compact composite scatters, which is often used in SAR image preprocessing [18]. When $N = 2$, the cosine model is called a cosine square law method. σ^0 is a function of $\cos^2 \theta$ [10,34]. It has good performance for ideal diffuse surfaces. However, it is not very suitable for surfaces with different scattering characteristics. The above two methods are suitable for specific ground object scattering characteristics. However, the scattering characteristics of ground objects have temporal and spatial variability. Therefore, a general method which is suitable for different scattering characteristics needs to be further explored [26].

2.2.2. The N Value under Different Growth Stages of Maize

The 12-view time series sentinel-1 (C-band) data were used to analyze the variation characteristics of σ^0 with θ at different growth stages of maize, with an interval of 1° (Figure 3). At first, it is assumed that the incidence angle dependence of σ_{vv}^0 and σ_{vh}^0 at C band is linear in the decibel range. The angle dependence of $\Delta\sigma^0$ (Table 1) is defined as $\Delta\sigma_{mean}^0 = (\sigma_{31}^0 - \sigma_{46}^0) / 15$ [7]. In the DOY of 109–181 and 277–289, σ_{vv}^0 and σ_{vh}^0 changed significantly with θ . For VV polarization, it is greater than 0.20 dB/° in 109–181 and 253–289 periods, and the maximum $\Delta\sigma_{mean}^0$ (0.52 dB/°) occurs at 133 days. For VH polarization, $\Delta\sigma_{mean}^0$ is greater than 0.20 dB/° in the 133–181 and 277–289 periods. The maximum $\Delta\sigma_{mean}^0$ (0.29 dB/°) occurs at 133 days. $\Delta\sigma_{mean}^0$ of VV is higher than that of VH, explains that the echo contribution of σ_{vv}^0 mainly comes from the first-order scattering in the distributed target, while the echo energy of σ_{vh}^0 mainly comes from the second-order and high-order scattering [35]. At 193–229 (VV) and 193–265 (VH), $\Delta\sigma_{mean}^0$ is obviously reduced to 0.08–0.15 dB/° and 0.06–0.18 dB/°, respectively. The correlation between σ^0 and θ becomes weaker during the tassel to silking period, and the change rate of $\Delta\sigma_{mean}^0$ becomes smaller. The results were confirmed by Wagner and Doninck [25,36]. The change of σ^0 with θ is sharp in bare soil stage, but slow in the tassel to silking period. In summary,

radar polarization combination and crop growth stage are important factors affecting the relationship between σ^0 and θ for maize.

Figure 3. The statistical relationship between radar backscattering coefficient (σ^0) and the incident angle from April to October. (a) VV polarization; (b) VH polarization.

Previous research conclusions and research data (Section 2.2.1) have confirmed that the cosine method with a constant N cannot adapt to the change of σ^0 for angle dependence with a different maize growth stage. Therefore, the dynamic N needs to be obtained for each time period (each scene). To calculate the N of each image, σ^0 is counted at 1° intervals. 16 angles (from 31° to 46°) are used as normalized angles. The original angle that is the same as the specific normalized angle does not participate in the normalization. The dark blue square on the diagonal in Figure 4 represents an empty combination. There are 16 normalized angles, and each normalized angle corresponds to the combination of 15 original angles. A total of 240 combinations of one image are considered (Figure 4). Therefore, 240 sets of observation data combinations are input to the least squares method to solve the optimal estimate of N based on Equation (1). Then, the N value suitable for any normalized angle (31° – 46°) of the specific scene image can finally be obtained.

Figure 4. The combination of normalized angle for least squares fitting.

The R^2 of fitting results for VV and VH is high. The R^2 of σ_{vv}^0 is greater than 0.88 except for the low R^2 of 229 days. The R^2 for σ_{vh}^0 at all time periods is greater than 0.69. In VV and VH polarization, the variation range of RMSE is 0.035–0.417 dB and 0.031–0.441 dB, respectively. Dynamic N is obtained (Table 2). The N of VV and VH polarization are 0.66–9.35 and 0.99–6.26 from April to October. The ratio of maximum and minimum N

values is approximately 14 and 6 for VV and VH polarization. N is significantly different at whole growth stages of maize. Optimized N is 0.66–3.35 and 0.99–3.32 for σ_{vv}^0 and σ_{vh}^0 during the tassel to silking period (DOY = 193–265), which is close to the range of N (N = 0, 1, 2) in the cosine methods, and N of our method is similar to Ulaby's method during the tassel to silking period [15].

Table 2. The fitted accuracy (R^2 and RMSE) and N value for σ_{vv}^0 and σ_{vh}^0 during DOY of 109–289, and the corresponding NDVI value was computed from Sentinel-2 reflectance.

Data	DOY	VV			VH			NDVI
		N	R^2	RMSE	N	R^2	RMSE	
2019-04-19	109	7.02	0.95	0.191	4.69	0.69	0.327	0.15
2019-05-13	133	9.35	0.91	0.417	6.26	0.72	0.441	0.17
2019-06-06	157	7.47	0.89	0.319	4.82	0.74	0.296	0.23
2019-06-18	169	4.22	0.90	0.142	3.68	0.96	0.074	0.27
2019-06-30	181	4.30	0.94	0.108	4.06	0.97	0.068	0.48
2019-07-12	193	2.90	0.98	0.042	3.32	0.97	0.054	0.71
2019-07-24	205	1.83	0.88	0.066	1.61	0.96	0.031	0.75
2019-08-17	229	0.66	0.24	0.110	0.99	0.81	0.046	0.83
2019-09-10	253	3.06	0.96	0.064	2.10	0.89	0.072	0.78
2019-09-22	265	3.35	0.99	0.035	3.09	0.99	0.037	0.59
2019-10-04	277	4.63	0.98	0.070	4.83	0.98	0.064	0.40
2019-10-16	289	5.85	0.97	0.122	4.61	0.91	0.151	0.28

2.2.3. Dynamic Cosine Method Based on NDVI

Crop growth stage is one of the most important factors affecting $\Delta\sigma^0$. The result of Section 2.2.2 confirmed that N is different during whole maize growth stages. In this case, NDVI is used to indicate the maize growth stage [37]. The response relationship between N_{vv} , N_{vh} , and NDVI in time series was statistically analyzed (Figure 5). N is larger in the low NDVI and smaller in the high NDVI for VV and VH polarization, meaning the variation of N is related to NDVI. This trend is closely related to the increase in the scattering from vegetation and the decrease in the scattering contribution from bare soil. Therefore, NDVI is used to model the dynamic changes of N.

Figure 5. Time series relationship between N_{vv} , N_{vh} , and NDVI. N_{vv} (N_{vh}) represents the N value under VV (VH) polarization.

Furthermore, the fitting relationship between N and NDVI is constructed in the software “Origin 2021”. The linear, logarithmic and exponential fits are selected to find the best fitting relationship. The N value (Table 2) and NDVI are input to the fitting formula (Equations (2), (3), and (4)), and the least square method is used to solve the fitting coefficient (a and b), and the coefficient with the smallest difference is defined as the best

fitting result. On the basis of previous studies, when a and b are obtained, a new dynamic cosine method which is suitable for the whole growth stage of maize is established.

$$N = a * NDVI + b \quad (2)$$

$$N = a * \ln(NDVI) + b \quad (3)$$

$$N = a * e^{b*NDVI} \quad (4)$$

N is the fitting results of σ_{vv}^0 and σ_{vh}^0 , and its value varies in different maize growth stages. a and b are the fitting coefficients. The fitting result will be described in detail in Section 3.1.

2.3. Validation Metrics

RMSE and bias are used to evaluate the error measures and improvement indexes of the method. Their expressions are as follows:

$$RMSE = \sqrt{(\sigma_{obs}^0 - \sigma_{norm}^0)^2} \quad (5)$$

$$Bias = (\sigma_{obs}^0 - \sigma_{norm}^0) \quad (6)$$

σ_{obs}^0 represents the backscattering coefficient observed by the satellite (dB); σ_{norm}^0 represents the normalized backscattering coefficient (dB); and “—” represents the average value.

3. Results

3.1. Relationship between N and $NDVI$

The fitted results showed that N and $NDVI$ have a good correlation in linear, logarithmic, and exponential relationships (Figure 6). For VH polarization, the linear relationship between N and $NDVI$ can be characterized better. The logarithmic relationship is better in VV polarization. However, the performance of linear and logarithmic relationships are slightly different for VV polarization. Hence, the fitting relationship between N and $NDVI$ obtained by the linear method is finally adopted in VV and VH polarization. The good correlation proves that $NDVI$ can well characterize the dynamic change of N , which is beneficial to the effective dynamic normalization of $\Delta\sigma^0$ during the entire maize growth stage.

Figure 6. Regression relationship between N and $NDVI$ for VV and VH polarization. (a) and (d): linear; (b) and (e): logarithmic; and (c) and (f): exponential.

3.2. The Comparison of Sentinel-1 Images before and after Normalization

According to the results of Section 3.1, the dynamic cosine method based on NDVI was established. The image of April 19th (DOY = 109) was selected for the bare soil period. The image of August 17th (DOY = 229) was selected during the tassel to silking period. The images from two periods were normalized to 40° and the effects before and after normalization using the dynamic cosine method were compared (Figures 7 and 8). In the bare soil period, the normalized image (Figure 7b) has good stability and does not change with θ . The raw radar image (Figure 7a) has a significant difference in the radar intensity at close (low incident angle) and long range (high incident angle). The radar echo is strong at close range, and will gradually weaken as it moves to long range. In addition, the radar data before and after normalization were selected to study the changes in σ^0 with θ . The average value of σ^0 is calculated for the study area at intervals of 1° . In Figure 7, the angle dependence of the normalized radar data is significantly reduced. At low θ , σ^0 decreases after normalization and this trend is opposite at high θ . In Figure 8, $\Delta\sigma^0$ is small during the tassel to silking period. σ_{obs}^0 and σ_{norm}^0 have little difference. However, the accuracy of σ_{norm}^0 has improved, comparing with σ_{obs}^0 . The newly proposed method can effectively improve the incidence angle effect of σ_{obs}^0 .

3.3. Performance Comparison of Three Normalization Methods

To compare the performance for first-order cosine method, cosine square law method and dynamic cosine method, three normalized reference angles (34° , 40° , and 44°) were selected. The results under different polarization and reference angles were analyzed.

The results of dynamic cosine method are in good agreement with σ_{obs}^0 (Figure 9). Regardless of the two polarizations or the three angles, the performance of dynamic cosine method is better than the other two methods. The results normalized to 34° and 44° are in the appendix (Figure A1). For the performance of the full growth stage of maize, the first-order cosine method and cosine square law normalization method performed well during the tassel to silking period (DOY:193–265). The normalization result at this stage is similar to the dynamic cosine method. During the bare soil period, the seedling emergence to tassel period and the maturity period (April, May, June, and October), σ_{norm}^0 based on first-order cosine method and cosine square law method are quite different from σ_{obs}^0 , and σ_{norm}^0 has a relatively large $\Delta\sigma^0$. The dynamic cosine method reduces $\Delta\sigma^0$ to a large extent and shows a good normalization effect.

The overall RMSE and bias normalized to 34° , 40° , and 44° for VV and VH polarization were calculated (Figures 10 and 11). This shows that the overall normalization ability of the dynamic cosine method based on NDVI is significantly better than the above two traditional methods. The overall RMSE and bias of the dynamic cosine method at VV polarization are 0.51 dB and 0.01 dB, respectively, which are 0.50 dB and -0.1 dB at VH polarization.

Figure 7. Comparison of VV polarizations for C bands showing the raw (a) and normalized (b) radar data (19th April, DOY = 109). (c) represents the radar data before and after normalization in the study area.

Figure 8. Comparison of VV polarizations for C bands showing the raw (a) and normalized (b) radar data (17th August, DOY = 229). (c) represents the radar data before and after normalization in the study area.

Figure 9. The comparison of σ_{obs}^0 and σ_{norm}^0 normalized to 40° by first-order cosine normalization, cosine square law normalization, and dynamic cosine method from April to October. (a) VV polarization; (b) VH polarization.

Figure 10. The RMSE and bias of first-order cosine method, cosine square law method, and dynamic cosine method (VV polarization). (a), (c), and (e) represent the RMSE for 34° , 40° , and 44° , respectively; (b), (d), and (f) respectively represent the deviation bias for 34° , 40° , and 44° .

Figure 11. The same as Figure 10 but for VH polarization.

The overall RMSE of first-order cosine method is 1.51 dB at VV polarization, and bias is -0.17 dB. The overall RMSE and bias of this method at VH polarization are 1.22 dB and -0.24 dB. The overall RMSE and bias of cosine square law method at VV polarization are 1.21 dB and -0.12 dB, respectively, which are 0.94 dB and -0.19 dB at VH polarization. In general, the overall performance of first-order cosine method does not perform well. When σ_{vv}^0 is normalized to 44° , the RMSE reaches the maximum value (4.01 dB) and the bias is -3.23 dB (Figure 10e,f). There is a significant negative deviation between σ_{norm}^0 and σ_{obs}^0 (Figure 12). Cosine square law method is slightly better than that of the first-order cosine method. When σ_{vv}^0 is normalized to 44° , the maximum RMSE is 3.56 dB, and the bias is -2.86 dB (Figure 10e,f). In addition, the maximum RMSE (1.43 dB) of the dynamic cosine method appears when σ_{vh}^0 is normalized to 44° (DOY = 133), and the bias is -1.11 dB. In different polarizations, maize growth stages and θ_{norm} combinations, comparing the overall and maximum RMSE of the three methods, can illustrate the advantages and disadvantages of the normalization method.

Figure 12. The influence of soil moisture and soil surface roughness parameter (root mean square height, RMSH) on N. (a) VV polarization; (b) HV polarization.

Based on the above analysis, the dynamic cosine method meets the normalization requirements of the incident angle better at different maize growth stages. Therefore, this new method tends to perform better than the other two methods.

4. Discussion

4.1. Dynamic Cosine Method Evaluation Within Different Crop Growth Periods and Radar Incidence Angles

A dynamic cosine method based on NDVI has been proposed, which is suitable for different growth stages of maize and the bare soil period (Figures 10 and 11). It expands the applicability of the cosine method. NDVI is used as a factor to characterize the growth stage of maize, and accurate angle normalization is achieved according to it. The results show that the applicability of the dynamic cosine method is different in the bare soil period and the non-bare soil period (Figures 10 and 11). In the bare soil period, the RMSE and bias of dynamic cosine method are larger than those in the non-bare soil period because NDVI is less sensitive to the bare soil period compared with the vegetation period. In addition, spring farming causes farmland blocks to be abnormally broken, and the roughness changes greatly in a short period of time. This is also an important factor affecting the performance of the dynamic cosine method in the bare soil period. The effect of roughness will be described in detail in Section 4.2.

The performance of the dynamic cosine method was evaluated by normalizing the time series SAR images to three representative θ_{norm} . The RMSE of σ_{vv}^0 normalized to 34° , 40° , and 44° is 0.51, 0.47, 0.55 dB, and bias is 0.12, -0.17 , and 0.08 dB, respectively. The RMSE of σ_{vh}^0 normalized to 34° , 40° , and 44° is 0.46, 0.48, and 0.58 dB, and bias is 0.08, -0.13 , and -0.26 dB. The RMSE of σ_{vv}^0 normalized to 40° is better than that of the other two

angles. The RMSE of σ_{vh}^0 normalized to 40° is slightly lower than the value of 34° , which is also an acceptable range. It is worth mentioning that the RMSE of σ_{vv}^0 and σ_{vh}^0 normalized to 44° both showed poor performance. However, with 40° as the normalized reference angle, the results of VV and VH polarization both performed better. Topouzelis et al. (2016) believed that the normalized method based on the cosine law usually works relatively well in the middle of the image, but does not perform correctly at the edges of the range direction [38]. This conclusion is applicable when θ_{norm} is the central θ of an image. The research results found that when θ_{norm} is determined, as the angle difference between θ and θ_{norm} increases the error of σ_{norm}^0 also increases. Therefore, the smaller the angle difference from θ_{norm} , the higher the accuracy of σ_{norm}^0 . Hence, when normalizing θ of an image, in order to balance the accuracy of σ_{norm}^0 for the entire image, the central θ is still the best choice for θ_{norm} . Generally speaking, the dynamic cosine method has greatly reduced this marginal error compared with the two traditional cosine normalization methods. It makes the RMSE of normalized result at the range edge (referring to a larger angle difference from θ_{norm}) within an acceptable range.

4.2. The Influence of Soil Surface Roughness and Soil Moisture on Radar Incidence Angle Effect

Roughness (root mean square height, RMSH) and soil moisture (SM) will affect the dependence of σ^0 and θ [15,39]. In the bare soil stage, to analyze the influence of RMSH and SM on our study, the IEM model was used to simulate σ^0 (VV and HV polarization) under different incident angles, different RMSH, and different SM. θ is set to 20° – 50° , and the interval is 10° ; the SM is set to 0.05 – $0.25 \text{ cm}^3/\text{cm}^3$, and the interval is $0.1 \text{ cm}^3/\text{cm}^3$; and the RMSH is set to 0.25 – 1.5 cm , and the interval is 0.25 cm . The correlation length is set to 10 cm . For the same SM and RMSH, σ^0 at different θ are fitted to obtain N (the method is the same as in Section 2.2.2) and the results of N are shown in Figure 12.

When analyzing the influence of the SM on N in the bare soil stage, the RMSH is fixed. For VV polarization, when the RMSH is less than or equal to 0.75 cm , N decreases with the increase in SM; when the RMSH is greater than 0.75 cm , the trend is the opposite. For HV polarization, N decreases with increasing SM, although this trend is weak. When the RMSH is fixed, the change of N caused by SM is 0.48 and 0.09 for VV and HV polarization, respectively. Therefore, it can be considered that the influence of SM on N is weak. When analyzing the influence of RMSH on N, the SM is fixed. For VV and HV polarization, N decreases as the RMSH increases. Under VV polarization, RMSH has a greater influence on N. When SM is $0.05 \text{ cm}^3/\text{cm}^3$, N corresponding to RMSH (0.25 – 1.5 cm) is 5.72 – 1.38 , and the change range of N is 4.34 . Under HV polarization, N is slightly affected by RMSH. When SM is $0.05 \text{ cm}^3/\text{cm}^3$, N corresponding to RMSH (0.25 – 1.5 cm) is 2.65 – 2.16 , and the variation range of N is 0.49 . This is quite different from the results obtained from satellite data (σ_{vh}^0). However, numerous studies have observed varying degrees of discrepancies between IEM simulations and SAR data in cross polarization. This discrepancy was related to the model itself [40–42].

The simulation experiment based on IEM proves that RMSH has an influence on N, and the influence of SM on N is negligible in the bare soil stage. In the sparse vegetation stage, the influence of vegetation is small, and the characteristics of the bare soil stage are assumed to be applicable in the sparse vegetation stage. N (Section 2.2.2) is obtained by empirical fitting based on the actual radar data in the study area. N mainly includes the influence of vegetation growth stage and part of the influence of RMSH in the bare soil stage. Most of the predecessors regard the RMSH as the focus on the radar incidence angle effect. However, the vegetation growth stage is an important factor affecting radar incidence angle effect, and it is also the focus of this research. The common mechanism of vegetation growth stage and RMSH on N and their specific contributions need to be further studied.

4.3. The Prospects of Dynamic Cosine Methods

The empirical relationship of the dynamic cosine method with the sentinel-1 C-band for maize, and other crops (such as wheat and soybeans) have similar relationships. The new method can even be used in other bands (L-band, X-band). The growth stages of maize can be well characterized by NDVI, which enables the dynamic cosine method based on NDVI to normalize the incidence angle effect at different maize growth stages. However, NDVI is obtained from optical images, which has the inherent defect of optical remote sensing. The effective acquisition of NDVI is limited to almost cloudless conditions, which limits its application in some cases. At present, the radar vegetation index shows great potential in capturing the crop phenological stages [43,44]. For example, the DpRVI (dual-pol radar vegetation index) proposed by Mandal based on Sentinel-1 SAR data can better characterize the growth status of soybeans, wheat, and other crops throughout the crop growth cycle [35]. The acquisition of DpRVI is not restricted by weather conditions (such as clouds and rain), and has great potential. Nevertheless, the applicability of DpRVI in maize needs to be further verified.

5. Conclusions

The normalization accuracy of first-order cosine method and cosine square law method cannot meet the requirements for normalization of the radar incident angle at different growth stages of maize. In order to solve this problem, a dynamic cosine method based on NDVI is proposed with the C-band SAR data (VV and VH polarization), and the accuracy of this method is compared with the traditional cosine method. The conclusion is as follows:

(1) Incidence angle effect ($\Delta\sigma^0$) is affected by maize seasonality. During the whole growth stage of maize, the power exponent N in the cosine method dynamically changes in time series SAR images. In the bare soil period (DOY: 109–181, 277–289), the range of N under VV polarization is 4.22–9.35, and under VH polarization is 3.68–6.26. In the vegetation period (DOY: 193–265), the range of N under VV polarization is 0.66–3.35, and under VH polarization is 0.99–3.32.

(2) There is a good correlation between N of dynamic cosine method and NDVI in the maize farmland area of Northeast China. NDVI can be used to parameterize changes in N . The three fitting results have good correlation, and NDVI can realize the dynamic normalization of the incident angle well.

(3) The dynamic cosine method based on NDVI greatly reduces the angular dependence, and has strong robustness in the entire growth stage of maize and different θ_{norm} . For VV polarization, the accuracy of the dynamic cosine method is 66% and 58% higher than that of the first-order cosine method and the cosine square law method, respectively. For VH polarization, the accuracy is improved by 59% and 47%.

At present, the dynamic cosine method based on NDVI performs well in verifying maize crops under C-band SAR data. The concept of dynamic cosine method is also applicable to other wavebands and ground object types. The detailed mechanism of action requires further study.

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Appendix A

Figure A1. Cont.

Figure A1. Comparison of three normalization algorithms from April to October. (a) is the normalization of VV polarization to 34°; (b) is the normalization of VH polarization to 34°; (c) is the normalization of VV polarization to 44°; (d) is the normalization of VH polarization to 44°.

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